Applied Energy 229 (2018) 493–504

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Integrated inexact energy systems planning under climate change: A case study of Yukon Territory, Canada

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HIGHLIGHTS

- A northern energy model has been developed for the Yukon Territory.
- Uncertainties and complexities in the Yukon energy system are discussed.
- The impact analysis of policy implementations is conducted.
- Optimal strategies are obtained for energy planning and GHG mitigation.

ARTICLE INFO

Keywords:
Energy modelling
System analysis
Optimization
Climate change
GHG emission

ABSTRACT

This study developed an inexact optimization modelling approach for supporting regional energy systems decision-making and greenhouse gas emission mitigation under uncertainty. The developed model integrates multiple inexact optimization programming approaches, incorporating interval linear programming, mixed-integer programming, and chance-constrained programming in an optimization framework. Uncertainties expressed as interval values and probabilistic distributions can be effectively handled. This is the first attempt that applies an optimization-based modelling approach to Yukon Territory, Canada. Three scenarios and one business-as-usual scenario are evaluated. System costs are minimized in this model. Results obtained from this model can help identify optimal patterns of renewable energy expansions in the Yukon. The interval solutions obtained could help decision makers to identify desirable renewable energy polices and emission reductions.

1. Introduction

Energy is an important input for social and economic development throughout the world. In recent decades, energy consumption and demands have increased exponentially globally as a result of population growth and economic development [1]. The energy demand-supply system faces risks of inevitable energy crises and environmental impacts. According to the Impacts of a Warming Arctic-Arctic Climate Impact Assessment, winter temperature in western Canada, including the Yukon, increased by as much as 3 °C to 4 °C between 1950 and 2000 [2,3]. Climate change has become one of the most serious issues that needs to be dealt with in the coming decades. Energy systems play an essential role in mitigating GHG emissions, which is widely acknowledged as the main factor leading to climate change [4]. To help develop a sustainable regional energy system which can meet the increasing energy demands with a low-carbon energy portfolio under climate change conditions, an effective planning of regional energy system is desired. Such planning should not only provide optimized energy resources allocation among end users, but also address the contradictions and interactions between economic development and environmental sustainability associated with energy system management [5]. However, energy system management is complicated by many systemic uncertainties from environmental, economic, as well as social factors [6,7]. Those uncertainties can be due to imprecise information, the random characteristics of natural events, and vague system objectives and constraints [8–11]. Failure to conduct uncertainty analysis may lead to less robust decision support. Thus, the formulation of an energy systems model for greenhouse gas (GHG) control under uncertainty is desired for supporting sustainable energy planning and climate change adaptation [12,13].

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https://doi.org/10.1016/j.apenergy.2018.06.140
Received 10 November 2017; Received in revised form 27 June 2018; Accepted 30 June 2018
Available online 20 August 2018
0306-2619/ © 2018 Published by Elsevier Ltd.

Nomenclature

Subscripts

i	Set of primary energy carriers ($i = 1, 2, ..., 7$)
g	Set of electrical generation technologies ($g = 1, 2, ..., 5$)
m	GHG emitter in the electricity generation processing ($m = 1, 2$)
j	Generating capacity-expansion options ($j = 1, 2, ..., 5$)
s	Set of energy end-user sectors ($s = 1, 2, 3, 4$)
t	Time period ($t = 1, 2, ..., 5$)

Decision variables

$XS_{i,t}^{\pm}$	Amount of energy resources i inputted during period t (GJ)
$XE_{g,t}^{\pm}$	Amount of electricity generated by technology g during period t (MWh)
$XE_{m,t}^{\pm}$	Amount of electricity generated by polluting emitter m during period t (MWh)
$AEL_{i,s,t}^{\pm}$	Energy resources i allocated to end-use sector s during period t (GJ)
$AEEL_{s,t}^{\pm}$	Amount of electricity allocated to end-user s during period t (MWh)
$y_{j,t}^{\pm}$	Integer variable identifying whether expansion option j undertaken during period t

Parameters

$CS_{i,t}^{\pm}$	Cost of energy sources i during period t (\$/GJ)
$CE_{g,t}^{\pm}$	Operating costs of electricity generation by technology g during period t (\$/MWh)
$CC_{j,t}^{\pm}$	Cost of electrical capacity expansion option j during period t (\$/MW)
$XC_{j,t}^{\pm}$	Capacity of electricity expansion option j during period t (MW)
IND_t	Carbon offset cost during period t (\$/kg)
$EF_{m,t}$	Emissions factor of electricity-generating technology m during period t (kg /MWh)
$AEF_{i,s,t}^{\pm}$	Emissions factor of primary energy i utilized in end-user s during period t (kg/GJ)
$DME_{i,s,t}^{\pm}$	Amount of energy resources i demanded by end-user s during period t (GJ)
$DMEE_{s,t}^{\pm}$	Electricity demanded by end-user s during period t (MWh)
F	Loss coefficient of energy-transmission process
STD_t	Maximum allowable GHG emissions during period t (kg)
$RES_{g,t}$	Residual capacity of electricity generation technology g during period t (MWh)
$T_{g,t}^{\pm}$	Operating time for generating technology g during period t (h)
$T_{j,t}^{\pm}$	Operating time for expanded-generating technology j during period t (h)
$UPCA_{g,t}^{\pm}$	Generating-capacity peak value of technology g during period t (MWh)
$UPGE_{g,t}^{\pm}$	Electrical-generation peak value of technology g during period t (MWh)
$(UPH_t^{\pm})^{p_i}$	Peak value of hydropower generation during period t under P_i level (MWh)
$(UPW_t^{\pm})^{p_i}$	Peak value of wind power generation during period t under P_i level (MWh)

Previously, optimization models have been widely used as an effective way to deal with many decision-making process in environmental management problems [14–18]. Optimizing energy system aims at minimizing total system costs and risks, and maximizing the overall system benefits. A number of multi-level modeling systems have been developed and applied to areas of multiple-scales. Among them, most optimization studies have been deterministic. For example, in past decades, Smith [19] proposed a linear optimization model for the planning of New Zealand's energy supply and distribution system, in which a conventional process analysis methods was applied and enabled a detailed representation of the energy-related activities under consideration. Groscurth et al. [20] developed a linear optimization model to evaluate potential energy savings from industry in several developed countries, including Germany, the United States, Netherlands, and Japan. Tiris et al. [21] developed a linear optimization model and a multi-attribute value model to coordinate long-term interactions among energy, the economy, and the environment in Turkey. Lin et al. [22] developed an optimization-based decision support system EMDSS, to provide comprehensive analyses of energy and environmental policy responses in the Toronto-Niagara Region (TNR), at Ontario Canada. Keirstead et al. [23] reviewed optimization models for urban biomass energy systems that provided selected technologies, operating rates, and supply infrastructures for a United Kingdom eco-town in five technology scenarios. More recently, many researchers have considered GHG emissions and the economy in energy system planning [24–26]. El-Fade et al. [27] investigated the range of energy-related GHG emissions and assessed mitigation options to reduce emissions, emphasizing the use of renewable energy. Blackjurst et al. [28] estimated energy costs, benefits, and GHG reductions and evaluated the trade-offs between program objectives and capital constraints through an optimization study applied in Pittsburgh and Austin in United States. Yu et al. [29] developed a stochastic programming model for regional power system planning in Jing-Jin-Ji, China under uncertainty. Galan et al. [30] develop a linear optimization model for states cooperation of power generation to meet the carbon emission commitment in U.S. It provided optimized cooperation approach as an action of Clean Coal Plan toward climate change mitigation.

Even though many studies have been conducted, most previous studies focused on the assumptions that associated system parameters such as energy price and demand may be reasonably simplified as deterministic inputs. However, many parameters for real-world cases are not known precisely, and need to be expressed as uncertain numbers, such as interval numbers or probabilistic distributions [31]. Many approaches have been proposed by previous studies for dealing with those uncertainties, including interval linear programming and stochastic mathematical programming. Also, though some studies were conducted with consideration of energy system planning, they did not fully considered the GHG emission control or uncertainties in renewable energy development [24,31–34]. There was a lack of systematic studies that address the energy system planning and climate change adaptation under uncertainty. Moreover, there have been very limited studies on high climate change risks, such as countries like Canada. Particularly, northern territories in Canada such as the Yukon Territory, also encounter severe energy supply shortages and risks. In the past, the Yukon Territory has relied on imported energy resources, which eventually have been limited by the exporter [35]. Thus, sufficient quantity and satisfactory quality for the Yukon energy system planning needs to be considered.

Therefore, as an extension of the previous efforts, the objective of this study is to develop an inexact chance-constrained mixed-integer regional energy model under climate change for the Yukon Territory in Canada. This model can reflect the tradeoffs between system benefits and environmental risks in the specific context of Arctic areas. It will thus help plan the energy system in Yukon, as well as manage the GHG emissions and renewable energy within an optimal framework. Uncertainties associated with various energy activities and renewable

energy availabilities within the study area will be addressed. In this study, chance-constrained programming, mixed-integer programming and interval programming were integrated in the energy system planning framework to tackle multiple uncertainties. Chance-constrained programming is used to tackle the uncertainties expressed as probability distributions. In energy system, renewable power availabilities are usually a random number, which would change due to many reasons, such as weather conditions and energy demands. Mixed-integer programming is integrated in this method due to its significance of dealing with integer variables. And Interval programming is chosen due to the nature of uncertain inputs derived from fluctuating market and imprecise information (such as natural gas price and demand). With the incorporation of interval programming, chance-constrained programming, and mixed-integer programming, the proposed model can address the uncertainty described as interval numbers and probability distributions in the regional energy system. The work aims at improving the conventional energy modeling method, which is not capable of reflecting uncertain information, and may no bet very useful due to absence of climate change considerations. The modeling results will provide decision support such as optimized energy system schemes and GHG emission controls for local decision-makers.

2. Study areas

The Yukon Territory occupies 482,443 km^2 in a triangular areas, which is located in northwestern Canada [36]. As shown in Fig. 1, it is bounded by the Beaufort Sea to the north and by British Columbia to the south. It abuts Alaska of the United States to the west and meets the Northwest Territories in the east. Yukon became a territory of Canada in 1898, and its population increased dramatically during the Klondike Gold rush from 1897 to 1899 [37]. The territory is made up of seven towns. The capital and largest town in the territory is Whitehorse, home to approximately two-thirds of the territory's population. In 2016, the population of Yukon was 37,642, accounting for 0.1% of Canada's total population [38]. Yukon also has a reservation for 14 First Nations, who make up 25% of the population.

Yukon has large unexplored and undeveloped deposits of primary energy resources, but almost all the fuels consumed in the Yukon are imported from the southern Canadian provinces [39]. Large shares of imported petroleum products are fuel oil for heating, transportation, and electricity generation. One of the characteristics of the Yukon electrical system is that it is isolated and disconnected with the North American grid, which makes it vulnerable to system failure. As shown in Table 1, Yukon's total generation capacity was at 140.6 MW, including 78 MW from hydropower, 61.8 MW from fuel-fired stations, and 0.8 MW from wind power [35]. For renewable energy resources, Yukon uses hydro, small amounts of solar, and wind power as renewable energy sources for electricity generation. Hydropower is the largest source of electricity generation in Yukon, with three established hydro plants with a capacity of 78 MW. The Yukon Energy Corporation (YEC) operates two wind farms on Haeckel Hill near Whitehorse, which are connected to the territorial electrical grid. The Yukon energy system is driven by demand from end users engaged in all kinds of activities. The transportation sector accounts for 37% of consumption in the form of refined petroleum products (primarily gasoline, diesel, and aviation fuels). Commercial and other institutional sectors are the territory's largest consumer of electricity. The remainder of energy demand is split

Table 1
Major primary energy and electricity sources: Canada and Yukon.

	Canada		Yukon	
	Energy	Electricity	Energy	Electricity
Non-renewable				
Crude oil	●	○	●	○
RPP	●	○	●	
Natural gas	●	○	●	
Coal	●	○	●	
Uranium	●	○		
Renewable				
Hydro power	●	○	●	○
Biomass	●	○	●	
Wind power	●	○	●	○
Geothermal	●		●	
Solar power	●		●	○

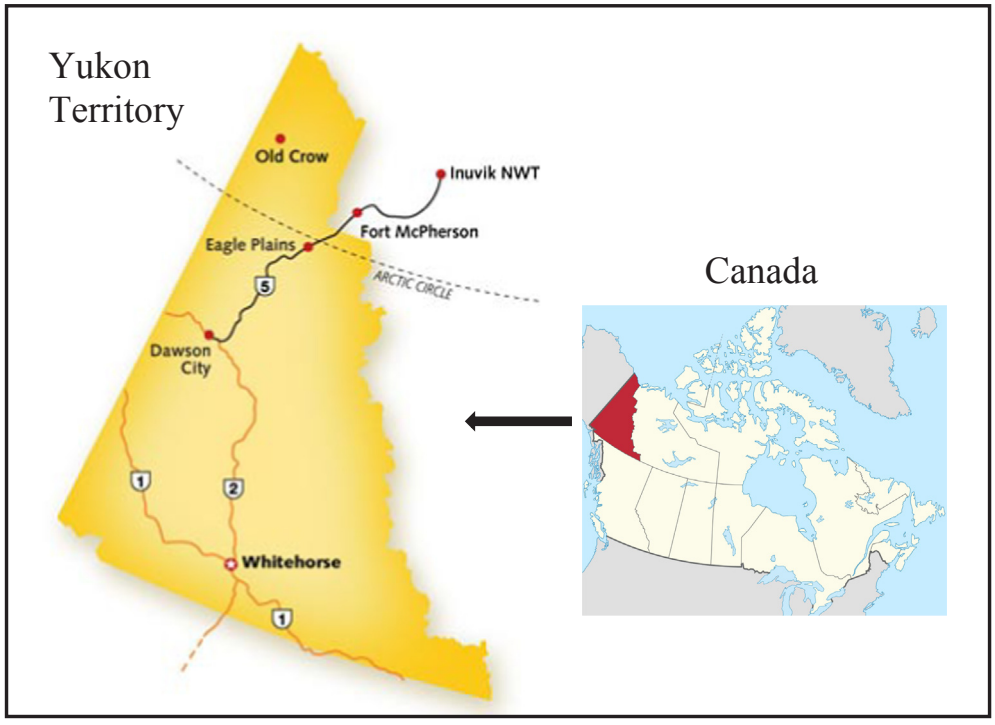

Fig. 1. Geographical reference map for Yukon.

among the residential, public administration, industrial, and agriculture sectors [39]. Industrial demand is noticeably influenced by the opening and closure of scattered industrial operations. Due to the fact of scarcely populated areas, energy costs are a major contributor to the high cost of living in Northern Canada. The per-capita energy cost in Yukon is twice the Canadian average, leading to a high cost of living in the Yukon [40].

Yukon's climate, in the broadest sense, is Continental Subarctic climate. The territory has the most variable climate in North America, with long, cold winters and short, warm summers [41]. The annual mean daily temperature is below zero in the territory, ranging from near zero in the south to approximately −10 °C in the far north and at higher elevations. The extreme temperatures in Yukon range as far apart as 98.9 °C. The record high of 36.1 °C occurred at Mayo, while Snag holds the record low of −62.8 °C, the lowest for the whole continent [42]. Meanwhile, climate change has influenced energy systems in Yukon significantly [43]. According to the Arctic Climate Impact Assessment, winter temperatures in western Canada, including the Yukon, increased by as much as 3–4 °C from 1950 to 2000 [2,3]. Rising GHG emissions are widely recognized as the main factor in climate change, especially global warming. Extreme cold winter and short days translate into high-energy demand. In Yukon, residents are highly insensitive energy consumers, especially in the northern latitudes. Therefore, given the geographical characteristics and intensive energy usage, a comprehensive understanding of the GHG emissions from all vectors of the Yukon energy matrix is very important.

In 2012, Yukon faced energy deficit of 200 MW [44]. Meanwhile, production at the active natural gas field at Kotaneelee has decreased by nearly 20% since 1999, from 60.9 million m^3 in 2009 to 51.6 million m^3 in 2012. These facts increase the risk of an energy shortage in the Yukon. Increasing demand for both electricity and primary energy forces decision makers to design an effective energy supply system, which considers capacity expansion alternatives, when demand rises beyond the capacity that existing facilities can supply. However, long-term reliability, grid integration ability, and economic feasibility of the electrical system in the Yukon has not been established. Thus, effective system planning for providing the optimized allocation of energy sources and expanding options for generating facilities is desired. Three issues in energy processes that should be considered in the energy system management framework are: energy supply, including electric conversion technologies; energy dispatch, which can be designed for efficient usage with less GHG emissions; and end users, where sufficient energy would be provided for demand sectors. Moreover, decision makers in Yukon Energy face challenges to meet the governmental expectations of renewable development and GHG reduction. In detail, the issues line up with the following aspects: (a) main energy supply and possible alternatives; (b) major emission contributors among energy-related activities; (c) major energy consumption of end-users; and (d) system costs with an increasing demand of energy. Thus, it is desired to develop a technology-detailed energy systems planning model to obtain maximized environmental benefits and minimized economic costs.

3. Methodology

3.1. ICMI model formulation

Due to the challenges in Yukon energy systems mentioned above, systematic analysis is desired to comprehensively analyze the energy system development under climate change. Optimization for energy system analysis has been used as a powerful tool for planning in many areas. In this study, a Yukon Energy Model will be developed for supporting energy system development. Based on the aforementioned Yukon energy system and the complexities in such systems planning, an interval chance-constrained mixed-integer programming (ICMI) method is introduced into an energy planning framework. ICMI is large-scale dynamic linear programming that is considered to be a reasonable approach for Yukon energy systems planning. It can be generalized into an interval chance-constrained linear programming as follows [45,46]:

$$Min\ f^{\pm} = C^{\pm}X^{\pm} \tag{1a}$$

subject to:

$$A^{\pm}X^{\pm} \geqslant (B^{\pm})^{p_i} \tag{1b}$$

$$X^{\pm} \geqslant 0 \tag{1c}$$

where $A^{\pm} \in \{R^{\pm}\}^{m\times n}$, $B^{\pm} \in \{R^{\pm}\}^{m\times 1}$, $C^{\pm} \in \{R^{\pm}\}^{1\times n}$, $X^{\pm} \in \{R^{\pm}\}^{n\times 1}$, and $R^{\pm}$ denotes a set of interval numbers.

In this model, the energy system includes three categories of activities: end-user activity, the electricity generation process, and supply of primary energy sources. Various energy carriers (coal, gasoline, and natural gas), diverse electricity generation technologies (hydropower, wind power, solar power, and bio-fuel power), and multiple end users (residential, commercial, transportation, and industrial sectors) are integrated into the optimization scheme. To deal with the uncertainties associated with possible renewable resources, interval programming, chance-constrained programming and mixed-integer programming are applied for the regional energy system in the Yukon. It can not only reflect uncertainties with less information as interval numbers, but also uncertain parameter with probability distribution (such as the accessibility of wind and solar power). The time horizon of the study is 25 years (2011–2035), which is divided into five planning periods, with five years in each period. The objective of this study to minimize the total system cost over the planning horizon, as constrained by the practical use of energy sources, electricity demand, and GHG emissions targets.

The total system costs in the ICMI model include costs of the primary energy supply, electrical generation, generating-technology expansion, and emissions sequestration. There are five categories of constraints: (1) the mass balance of primary energy resources necessary for the primary energy supply to satisfy demand; (2) the electricity balance within the grid system; (3) the emissions constraint controlling the GHGs emitted by energy-consuming activities and the generating process; (4) the capacity of energy supplies limited by social economic, technical, and environmental conditions; (5) the integer variables of the capacity expansion options; and (6) non-negative decision variables. Thus, the inexact Yukon energy model can be formulated as follows.

$$Min\ f^{\pm} = C_1^{\pm} + C_2^{\pm} + C_3^{\pm} + C_4^{\pm} \tag{2a}$$

1. Costs for supply of primary energy sources

$$C_1^{\pm} = \sum_{i}^{7}\sum_{s}^{4}\sum_{t}^{5} CS_{i,s,t}^{\pm} \times XS_{i,s,t}^{\pm} \tag{2b}$$

2. Cost for electricity generation

$$C_2^{\pm} = \sum_{g}^{5}\sum_{t}^{5} CE_{g,t}^{\pm} \times XE_{g,t}^{\pm} \tag{2c}$$

3. Capital costs for expansion of generating-technology capacity

$$C_3^{\pm} = \sum_{j}^{5}\sum_{t}^{5} XC_{j,t}^{\pm} \times CC_{j,t}^{\pm} \times y_{j,t}^{\pm} \tag{2d}$$

4. Costs for emission sequestration

$$C_4^{\pm} = \sum_{t}^{5} IND_t \times \left(\sum_{m}^{2} XE_{m,t}^{\pm} \times EF_{m,t} + \sum_{i}^{7}\sum_{s}^{4} AEL_{i,s,t}^{\pm} \times AEF_{i,s,t}^{\pm}\right) \tag{2e}$$

subject to:

(a) Mass balance of primary energy resources

$$DME^{\pm}_{i,s,t} \leqslant AEL^{\pm}_{i,s,t} \quad \forall\, i, s, t \tag{2f}$$

$$AEL^{\pm}_{i,s,t} \leqslant XS^{\pm}_{i,s,t} \times F \quad \forall\, i, s, t \tag{2g}$$

(b) Mass balance of electricity

$$DMEE^{\pm}_{s,t} \leqslant AEEL^{\pm}_{s,t} \quad \forall\, s, t \tag{2h}$$

$$\sum_{s}^{4} AEEL^{\pm}_{s,t} \leqslant \sum_{g}^{5} XE^{\pm}_{g,t} \times F \quad \forall\, t \tag{2i}$$

(c) Emissions control constraint

$$\sum_{m}^{2} XE^{\pm}_{m,t} \times EF^{\pm}_{m,t} + \sum_{i}^{7}\sum_{s}^{4} AEL^{\pm}_{i,s,t} \times AEF^{\pm}_{i,s,t} \leqslant STD_t \quad \forall\, t \tag{2j}$$

(d) Capacity constraint

$$\sum_{g}^{5} RES_{g,t} \times T^{\pm}_{g,t} + \sum_{j}^{5} y^{\pm}_{j,t} \times XC^{\pm}_{j,t} \times T^{\pm}_{j,t} \leqslant \sum_{g}^{5} XE^{\pm}_{g,t} \quad \forall\, t \tag{2k}$$

$$\sum_{g}^{5} RES_{g,t} + \sum_{j}^{5} y^{\pm}_{j,t} \times XC^{\pm}_{j,t} \leqslant \sum_{g}^{5} UPCA^{\pm}_{g,t} \quad \forall\, t \tag{2l}$$

$$(RES_{wind,t} + y^{\pm}_{wind,t} \times XC^{\pm}_{wind,t}) \times T^{\pm}_{wind,t} \leqslant (UPH^{\pm}_{t})^{p_i} \quad \forall\, t \tag{2m}$$

$$(RES_{solar,t} + y^{\pm}_{solar,t} \times XC^{\pm}_{solar,t}) \times T^{\pm}_{solar,t} \leqslant (UPW^{\pm}_{t})^{p_i} \quad \forall\, t \tag{2n}$$

$$XE^{\pm}_{g,t} \leqslant UPGE^{\pm}_{g,t} \quad \forall\, g, t \tag{2o}$$

(e) Technology constraints

$$XS^{\pm}_{i,s,t} \geqslant 0 \quad \forall\, e, t \tag{2p}$$

$$XE^{\pm}_{g,t} \geqslant 0 \quad \forall\, g, t \tag{2q}$$

$$XE^{\pm}_{m,t} \geqslant 0 \quad \forall\, m, t \tag{2r}$$

$$AEL^{\pm}_{i,s,t} \geqslant 0 \quad \forall\, i, s, t \tag{2s}$$

$$AEEL^{\pm}_{s,t} \geqslant 0 \quad \forall\, s, t \tag{2t}$$

$$y^{\pm}_{j,t}\begin{cases} = \text{integer}, & \text{if the expansion of generation technology } g \text{ is undertaken,} \\ = 0, & \text{otherwise} \end{cases} \quad \forall\, j, t \tag{2u}$$

The solution algorithm was developed by Huang G. to solve interval programming problems by analyzing the interactions between the decision variables and the parameters in the objective function and constraints [47]. The solution algorithm process the inexact model through two sub-models. The first step is to formulate and solve the lower bound sub-model f^{-}, when the objective function is minimized. And then, the upper bound sub-model f^{+} can be formulated and solved based on the results of the first sub-model. For n interval variables $X^{\pm}_{j}(j = 1, 2, ..., n)$, if k_1 of them are positive and k_2 of them are negative, let the k_1 coefficients $c^{\pm}_{i} \geqslant 0 (j = 1, 2, ..., k_1)$, and the latter k_2 coefficients $c^{\pm}_{i} \leqslant 0 (j = k_1 + 1, k_1 + 2, ..., k_1 + k_2)$, where $k_1 + k_2 = n$ [48]. It is assumed that $b^{+}_{i} > 0$ and $f^{\pm} > 0$ in this study. Then, the lower bound sub-model can be formulated as:

$$Min\ f^{-} = \sum_{j}^{k_1} C^{-}_{j} X^{-}_{j} + \sum_{j=k_1+1}^{n} C^{-}_{j} X^{+}_{j} \tag{3a}$$

subject to:

$$\sum_{j}^{k_1} |a_{ij}|^{+} Sigh(a^{+}_{ij}) x^{-}_{j} + \sum_{j=k_1+1}^{n} |a_{ij}|^{-} Sigh(a^{-}_{ij}) x^{+}_{j} \geqslant b_i(t)^{(p_i)}, \forall\, i \tag{3b}$$

$$X^{\pm}_{j} \geqslant 0, \forall\, j \tag{3c}$$

The solution of this model can be obtained as $X^{-}_{j\,opt} (j = 1, 2, ..., k_1)$, $X^{+}_{j\,opt} (j = k_1 + 1, k_1 + 2, ..., n)$ and f^{-}_{opt}. Then, the lower bound sub-model corresponding to f^{+} can be formulated as follows:

$$Min\ f^{+} = \sum_{j}^{k_1} C^{+}_{j} X^{+}_{j} + \sum_{j=k_1+1}^{n} C^{+}_{j} X^{-}_{j} \tag{4a}$$

subject to:

$$\sum_{j}^{k_1} |a_{ij}|^{-} Sigh(a^{-}_{ij}) x^{+}_{j} + \sum_{j=k_1+1}^{n} |a_{ij}|^{+} Sigh(a^{+}_{ij}) x^{-}_{j} \geqslant b_i(t)^{(p_i)}, \forall\, i \tag{4b}$$

$$X^{\pm}_{j} \geqslant 0, \forall\, j \tag{4c}$$

$$X^{+}_{j} \geqslant (X^{-}_{j})_{opt}, j = 1, 2, ..., k_1 \tag{4d}$$

$$X^{-}_{j} \leqslant (X^{+}_{j})_{opt}, j = k_1 + 1, k_1 + 2, ..., n \tag{4e}$$

The solution of the upper bound model then can be accessed by solving sub-model (4). Therefore, the final solution can be obtained, which is $f^{\pm}_{opt} = [f^{-}_{opt}, f^{+}_{opt}]$ and $X^{\pm}_{jopt} = [X^{-}_{jopt}, X^{+}_{jopt}]$.

In general, the steps of this algorithm can be summarized as follows:

Step 1. Define the distribution information $B(t)$, and select a set of p_i values for the constraints. Then, the corresponding value can be obtained according to $B(t)^{p_i}$.
Step 2. Formulate the lower bound model of f^{-}, with both the objective function and the constraints corresponding to p_i levels.
Step 3. Solve the lower bound model f^{-}. Obtain $(X^{-}_{j})_{opt} (j = 1, 2, ..., k_1)$, $(X^{+}_{j})_{opt} (j = k_1 + 1, k_1 + 2, ..., n)$, and $(f^{-})opt$.
Step 4. Formulate the upper bound model of f^{+}, with both the objective function and the constraints corresponding to p_i levels based on the solution of the lower bound model.
Step 5. Solve the upper bound model f^{+}. Obtain $(X^{+}_{j})_{opt} (j = 1, 2, ..., k_1)$, $(X^{-}_{j})_{opt} (j = k_1 + 1, k_1 + 2, ..., n)$ and $(f^{+})_{opt}$.
Step 6. Obtain the model solution of $(X^{\pm}_{j})_{opt}$ and $(f^{\pm})_{opt}$.
Step 7. Stop.

3.2. Scenario design

Based on the goals of renewable development and GHG emission reductions, three scenarios and a business-as-usual (BAU) case were designed, based on strategies developed by the Yukon Government. In scenario 1, by 2020, GHG emissions levels in Yukon would reduce 20% from 2006 levels in accordance with the Climate Change Action Plan issued by the Yukon government in January 2009. In scenario 2, the supply of renewable energy would increase by 20% by 2020 following the Energy Strategy for the Yukon. In scenario 3, the targets for both GHG emissions and the renewable energy supply would be met. In the BAU case, there will be no exogenous restrictions on emission reduction, nor renewable energy development. The impacts of different scenario setting on total system costs and GHG emissions can be assessed. Moreover, it is assumed in the model that, in these three scenarios, if GHG emissions exceed the emissions standard, the carbon offset credit will be purchased from other jurisdictions. Thus, violations of GHG emission constraints will result in more system costs. To make the model sufficiently general and accurate, the following assumptions and simplifications were made. The electricity generation facilities operates properly without restriction of lifetime and retirement; equipment breakdowns were not explicitly considered. Even though the assumptions are justified through practical conditions, they may still cause bias embedded in alternative of decision making, such as value-

laden in electricity generation facilities that are facing retirement, or overuse of facilities that are temporarily breakdown. The new power plants will start producing electricity in the same period the expanded capacity is constructed; GHG emissions are of CO_2 equivalent. Lastly, a time horizon of 5 years was used throughout this study.

4. Result analysis and discussion

In this study, the ICMI model deals with energy related activities in an uncertain environment. The obtained solutions effectively reflect a complete energy management system from electricity generation and resource allocation to energy utilization. These solutions can also provide a technology-rich energy systems plan for policy makers. Such planning provides a bridge between regulated policies and associated economic and environmental impacts in the Yukon. The optimized energy systems under different scenarios are provided as multiple solutions for the decision makers. Moreover, the analysis of tradeoffs regarding environmental protection and economic costs could provide a scientific basis for policy making. Overall, the results are obtained by solving the ICMI model using the interactive solution algorithm previously described. The energy dispatch planning, power generation schemes, system costs, GHG emissions by sectors, and generating technology expansion in the BAU and three policy scenarios can be generated to reflect the impacts of existing policies and support future decision making.

4.1. BAU case

In the Yukon energy system, the territory poses a demand for primary energy and electricity. Energy sources used to meet the demand in the Yukon area are natural gas, biomass, light fuel, heavy fuel, gasoline, diesel, and aviation fuel. Electricity generating sources include hydropower, diesel, wind, solar, and biomass. Given the choices of alternatives identified, the model chooses the lowest-cost set of options to meet the specified energy demand. In the BAU case, there are executed regulatory, economic/political targets, or environmental measures considered, which means the ICMI was run without exogenous constraints. These targets and measures including the energy supply requirement, energy transmission availabilities, capacity expansion options and GHG emissions standard. Through integrating the related target and requirement in the model, constraints of energy demand/supply balance, GHG emission control, and capacity expansion are designed. The results for the BAU case show the pattern of resource production and development over time without GHG emissions, nor renewable energy development constraints.

The results for primary energy supply are presented in Table 2. Total primary energy consumed in the study region will be [50,842, 53,261] GJ, [53,234, 56,601] GJ, [55,627, 58,573] GJ, [57,292, 60,659] GJ, [58,309, 62,308] GJ over five study periods. The Commercial sector is shown to be the major energy consumer in Yukon's energy system. The energy supplied to this sector would be from [34,737, 35,157] GJ in period 1 to [38,731, 39,572] GJ in period 5, with a growth rate of [4%, 9%]. Natural gas and light fuel are mainly used for space heating, cooling, water heating, and auxiliary motors in commercial and institutional buildings. The transportation sector would be the second largest energy consumer and the fastest-growing sector. Due to the distributed and remote residencies, the Yukon shows a greater dependency on private vehicles and aviation. The total energy consumed would increase from [12,737, 14,105] GJ in period 1, to [16,947, 20,105] GJ in period 5. This increase rate from period 1 to 5 would be [56%, 58%] in gasoline, [35%, 45%] in diesel, and [17%, 29%] in aviation fuel. The usage of gasoline would increase at the highest rate in the transportation sector. Such an increase would be caused by the increasing number of vehicles and higher demand for on-road gasoline. The primary energy for the residential sector shows a stationary phase from period 1 to 5. After Yukon's population grew by 11.7% between 2006 and 2011, which outpaced the nation, the population growth rate has decreased ever since, and will keep in a stable status. This fact will result in a steady usage of energy. In the residential sector, biomass is mainly used for space heating from burning wood and organic matter. Light fuel oil is either kerosene or light fuel oil, mainly used for off-road applications such as generators, heating and cooling. The industrial sector used the least energy compared with the other three sectors, and the amount will decrease from period 1 to 2, and then keep stationary after period 3. Yukon's major industry is mining and tourism, followed by traditional industries of trapping and fishing. The territory is considered an oil and gas frontier area with minor industrial development. The decrease of energy usage in the industrial sector is due to the downward trend and gradual closure of mines with declining mineral prices.

Electricity demand in the Yukon will increase along with the population and economic development. Fig. 2 shows the majority of electricity will be allocated to the commercial sector, which will account for [56%, 58%] of the total electricity generated in the five periods. The amount of electricity consumed by the commercial sector will increase with time from [972, 1,023] MWh in period 1, to [1,111, 1,684] MWh in period 5, with a growth rate as much as 60%. The commercial users of energy in the Yukon include offices, school, health care, and mercantile buildings. These end-users will also result in higher demands during daily peak periods. The residential sector will consume [39%, 42%] of the total electricity, which will also increase gradually with growth rate around 40%. Households use energy to heat, cool, light, and run appliances, especially in the long, cold winters. The industrial sector will use a small amount of electricity for mining. Transportation will barely consume electricity, which is in line with the current status in the Yukon. This sector might use more electricity with time due to the development of hybrid technologies for private and public transportation. The average percentage means the average number of upper and lower bound to the total electricity generated in one period. The dotted line in Fig. 2 shows a stabilized tendency, except for the decrease of electricity used in the industrial sector due to the policy of closing mines in the Yukon.

4.2. Scenario analysis

The results obtained regarding the generating capacity expansion,

Table 2
Primary energy supply by sector during five study periods (GJ).

	Period 1	Period 2	Period 3	Period 4	Period 5
Residential					
Biomass	526	526	526	526	526
Light fuel	1578	1578	1578	1578	1578
Total	2105	2105	2105	2105	2105
Commercial					
Natural gas	[4316, 4737]	[4211, 4737]	[4211, 4737]	[4211, 4737]	[4211, 5053]
Light fuel	30,421	32,707	33,522	34,134	34,520
Total	[34,737, 35,157]	[36,918, 37,444]	[37,733, 38,258]	[38,345, 38,871]	[38,731, 39,572]
Industrial					
Natural gas	947	316	0	0	0
Heavy fuel	[316, 947]	526	526	526	526
Total	[1263, 1894]	[316, 842]	526	526	526
Transportation					
Gasoline	[1684, 2000]	[2105, 2315]	[2105, 2631]	[2632, 2842]	[2632, 3157]
Diesel	[7895, 8421]	[8526, 9789]	[9474, 10,842]	[10,000, 11,684]	[10,632, 12,210]
Aviation fuel	[3158, 3684]	[3263, 4105]	[3684, 4210]	[3684, 4631]	[3684, 4736]
Total	[12,737, 14,105]	[13,895, 16,210]	[15,263, 17,684]	[16,316, 19,157]	[16,947, 20,105]

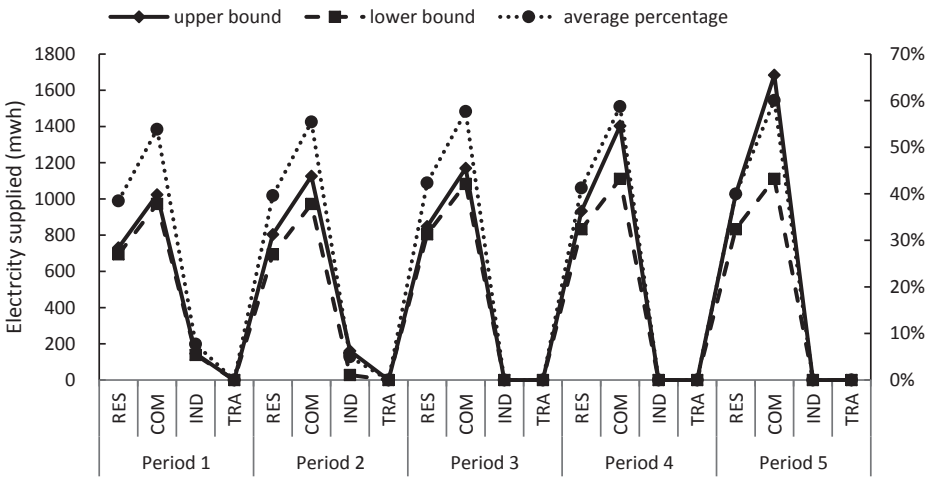

Fig. 2. Electricity supply by end-user sector (MWh).

greenhouse gas emission mitigation under the BAU and three other scenarios, and their associated system costs are presented in Tables 3–5, and Figs. 3 and 4. Firstly, over 25-year horizon, the generating capacity will be expanded to meet the increasing electricity demand. The expansion options are applied to the existing generating technologies, including hydropower plants, diesel power plants, wind turbines, solar panels, and biomass power plants. However, the power plants' aging and underperformance are not considered in expansions. Table 3 and Fig. 3 present the solutions of capacity expansion in BAU and three scenarios. In scenario 1, the GHG emissions will be 20% below 2006 levels by 2020. The total capacity expansion pattern in scenario 1 is similar to that in the BAU case due to the similar economic development prediction. Renewable energy technologies, particularly wind power, will be expanded depending upon the GHG reduction requirements and electricity demand increase. This also shows that the optimal expansion of renewable energy capacity could meet the increased electricity demand. Wind and biomass power will be expanded by [12, 17], and [10, 25] MW, respectively. Hydro power is the most preferable option to expand electricity generation, because Yukon's mountainous terrain and wealth of rivers and lakes are ideal for hydro-electric generation. The model provides [60, 60], [0, 0], [7.5, 10], [0, 0], [7.5, 10] MW of capacity expansion in both the BAU case and scenario 1 during the five periods. Diesel-fired capacity will be the second most preferable expansion technology because of the competitive construction costs for conventional generating technology, and would account for [44, 48] MW over the study period. In scenario 2, Yukon's renewable energy increases 20% by 2020. Table 3 illustrates the construction of expanded capacity in scenario 2 and the BAU case. The optimal capacity expansion pattern in scenario 2 would be similar to the BAU case, but the construction period would be slightly different. Hydropower will still be the most preferable option to increase electricity generation, accounting for [37.5, 40], [22.5, 30], [7.5, 10], [0, 0], and [7.5, 10] MW of capacity expansion during the five study periods of scenario 2. Compared to the BAU case, construction activity will be decentralized, mainly because of the emphasis on the renewable-energy policy requirements. Diesel-fired facilities will expand their capacity by the second largest amount, accounting for [44, 48] MW over the study period. Renewable resources such as hydro and wind power will increase from [17, 80] MW in BAU to [21, 90] WM in Scenario 2. Scenario 3 presents a case in which by 2020, Yukon's renewable energy share has increased by 20%, GHG emissions have fallen 20% below 2006 levels, and a similar expansion scheme to scenario 2 is presented. Hydro plant, diesel-fired plant and wind plant will be first chosen as expanded facilities in period 1. These result underline that the renewable energy policy will be the critical influence to achieve the GHG emission target. In this case, scenario 3 will show a satisfaction of both scenario 1 and 2.

In the planning horizon, GHG emissions will be mainly produced by the primary energy sectors. As shown in Table 4, the GHG emitted by primary energy users will increase steadily from 2011 through 2035 during the five study periods. The maximum emitted GHG would occur in period 5 with [1,698, 1,983] kilotonnes of GHG released into the atmosphere. The upper and lower bounds of each sector's share of GHG emissions during five periods are shown. Among four end users, the transportation sector will be the largest source of GHG emissions, accounting for [64%, 74%] of the total GHG emitted by fossil fuels and natural gas. The commercial sector will be the second largest, followed by the residential and industrial sectors.

The results of GHG emissions by power generation under different scenarios are presented in Table 5. From 2011 to 2035, total GHG emissions will remain stable. Energy development and use will result in emissions of [9,126, 9,463] kilotonnes and [9,007, 9,369] kilotonnes in the BAU case and scenario 1, respectively. In Scenario 1, Yukon's GHG emissions are 20% below 2006 levels by 2020. This scenario assumes that a carbon credit market will be established. If GHG emissions exceed their limits, extra carbon credits will be purchased, resulting in

Table 3
Solutions of capacity expansion in BAU and there scenarios.

	Period 1	Period 2	Period 3	Period 4	Period 5
BAU					
Hydro	[6, 8]	0	1	0	1
Diesel	[6, 11]	0	0	0	0
Wind	[3, 6]	1	1	0	0
Solar	0	0	0	0	0
Biomass	0	1	0	0	0
Scenario 1					
Hydro	[6, 8]	0	1	0	1
Diesel	[5, 10]	1	0	0	0
Wind	[3, 6]	1	1	0	0
Solar	0	0	0	0	0
Biomass	1	0	0	0	0
Scenario 2					
Hydro	[4, 5]	3	1	0	0
Diesel	[3, 5]	[3, 6]	0	0	0
Wind	[2, 4]	1	1	1	1
Solar	0	0	0	0	0
Biomass	0	1	0	0	0
Scenario 3					
Hydro	[4, 5]	3	1	0	0
Diesel	[3, 5]	[3, 6]	0	0	0
Wind	[2, 4]	1	1	1	1
Solar	0	0	0	0	0
Biomass	0	1	0	0	0

Table 4
GHG emissions by energy source during the five study periods (kilotonne).

End users	Energy	Period 1	Period 2	Period 3	Period 4	Period 5
Residential	Biofuel	11	11	11	11	11
	Light fuel	115	115	115	115	115
Commercial	Natural gas	[91, 99]	[88, 99]	[88, 99]	[88, 99]	[88, 99]
	Light fuel	223	239	245	250	253
Industrial	Natural gas	48	16	0	0	0
	Heavy fuel	[23, 70]	[0, 39]	[0, 39]	[0, 39]	[0, 39]
Transportation	Gasoline	[119, 141]	[149, 164]	[149, 186]	[186, 201]	[186, 223]
	Diesel	[583, 621]	[629, 722]	[699, 800]	[738, 862]	[785, 901]
	Aviation fuel	[223, 260]	[231, 290]	[260, 298]	[260, 327]	[260, 335]

Table 5
GHG emissions by source of power generation in the BAU case and three scenarios (kilotonne).

	Emitter	BAU	Scenario 1	Scenario 2	Scenario 3
Period 1	Diesel	[1754, 1812]	[1697, 1697]	[1409, 1467]	[1409, 1467]
	Biomass	[64, 64]	[73, 85]	[64, 64]	[64, 64]
Period 2	Diesel	[1754, 1812]	[1754, 1812]	[1754, 1812]	[1754, 1812]
	Biomass	[73, 85]	[73, 85]	[73, 85]	[73, 85]
Period 3	Diesel	[1754, 1812]	[1754, 1812]	[1754, 1812]	[1754, 1812]
	Biomass	[73, 85]	[73, 85]	[73, 85]	[73, 85]
Period 4	Diesel	[1754, 1812]	[1754, 1812]	[1754, 1812]	[1754, 1812]
	Biomass	[73, 85]	[73, 85]	[73, 85]	[73, 85]
Period 5	Diesel	[1754, 1812]	[1754, 1812]	[1754, 1812]	[1754, 1812]
	Biomass	[73, 85]	[73, 85]	[73, 85]	[73, 85]
Total		[9126, 9463]	[9007, 9369]	[8781, 9118]	[8781, 9118]

higher system costs. The regular rate became effective after 2011. Over the 25-year horizon, GHG emissions from electricity generation will mostly come from thermal facilities. The majority of GHG emissions will be produced by diesel-fired facilities, accounting for [1,697, 1,697], [1,754, 1,812], [1,754, 1,812], [1,754, 1,812], and [1,754, 1,812] kilotonnes in each period, or 96% of total emissions from electricity generation. By 2035, GHG emissions from electricity generation will total [1,754, 1,812] kilotonnes. Compared with the BAU, GHG emissions for scenario 1 will decrease by 1.3% due to policy constraints, reflecting the efficiency of policy controls, thus total GHG emissions will decrease by [94, 119] kilotonnes. The GHG emissions in scenario 3 and scenario 2 will be no less than the emissions for scenario 1. Thus it is concluded that these two scenarios will satisfy GHG emissions reduction targets at the same time. Moreover, scenario 3 will satisfy the renewable energy planning requirement as defined for scenario 2. Therefore, it can be conclude that the renewable energy policies will effectively support both sustainable energy development and GHG emissions restrictions. However, a GHG mitigation policy would restrict emissions only to a certain extent.

The costs for the entire system are detailed in Fig. 4, including fuel costs, fixed and variable operational costs for new and existing power stations, capital costs for the construction of expanded generating technologies, and the costs of carbon credits. In Fig. 4, it is shown that the system costs will be $[3,706, 4,990], $[3,726, 5,018], $[3,701, 4,996], and $[3,726, 5,024] million CAD under the BAU case and scenarios 1, 2, and 3, respectively. The highest system costs will be under scenario 3, in which the GHG mitigation and renewable energy resource exploitation and development goals are all satisfied. Scenario 1 results in the second-highest system cost because the GHG mitigation restrictions may require purchases of carbon credits from other jurisdictions. On the other hand, the BAU case incurs a relatively lower cost. Environmental and energy system factors are not considered in the BAU case, and the system cost would be less in this situation. Thus, this scenario analysis reflects tradeoffs among system costs, environmental benefits, and energy conservation.

In Fig. 5, the policy implementation recommendation with according system costs shows the potential policies and strategies to implement three scenarios. To achieve a clean energy systems with minimized cost, Scenario 2 will provide best outcomes with both low GHG emissions and low system cost. Such results can be realized

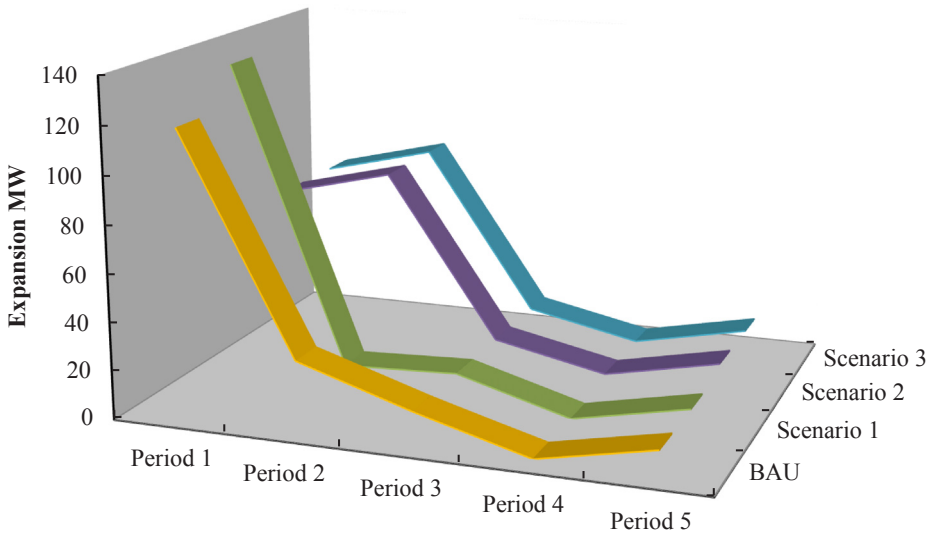

Fig. 3. Capacity expansion scheme in BAU and three scenarios.

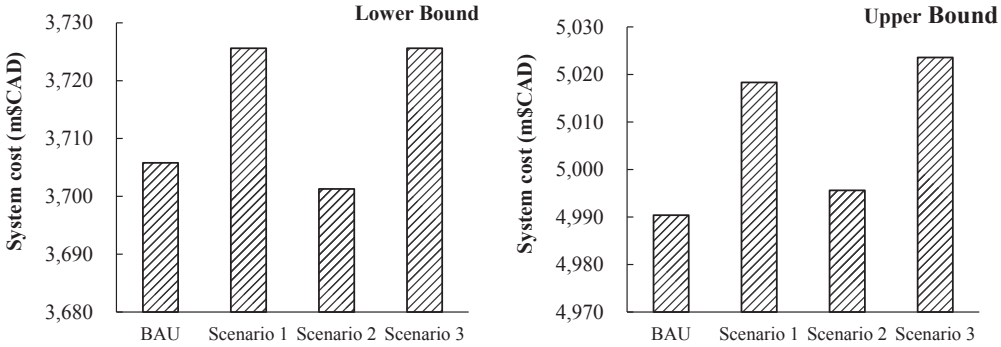

Fig. 4. Total system costs under the three scenarios and the BAU case (a) upper bound (b) lower bound (million CAD$).

through renewable energy penetration, thus renewable stimulation strategies and policies could be made to enlarge the environmental and economic benefits.

4.3. Uncertainty analysis

In the ICMI model, P_i levels represent the probabilities of constraint violation. System certainty can be increased by an increased risk of system failure. To study the impact of diverse P_i values on the energy system, three levels of P_i were analyzed, as shown in Fig. 6. It is indicated that system costs are similar, except in the solution for the upper sub-model, reflecting the same pattern of primary energy production and consumption. However, the capacity expansion schemes vary slightly based on the desired system reliability. Hydro power will provide [60, 60], [0, 0], [7.5, 10], [0, 0], [7.5, 10] MW during the five study periods under $P_i = 0.01$, while [75, 80] MW in period 1 under

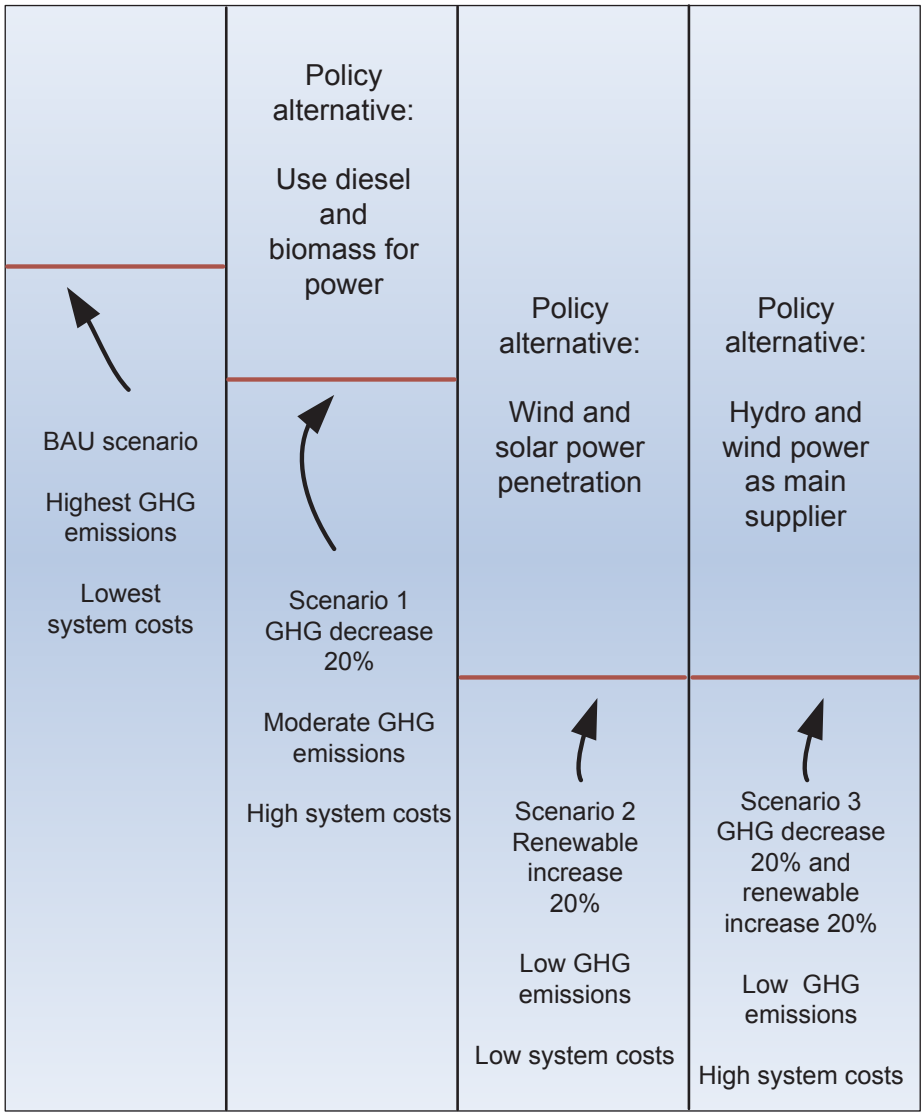

Fig. 5. Policy implementation recommendations with system investment under different scenarios.

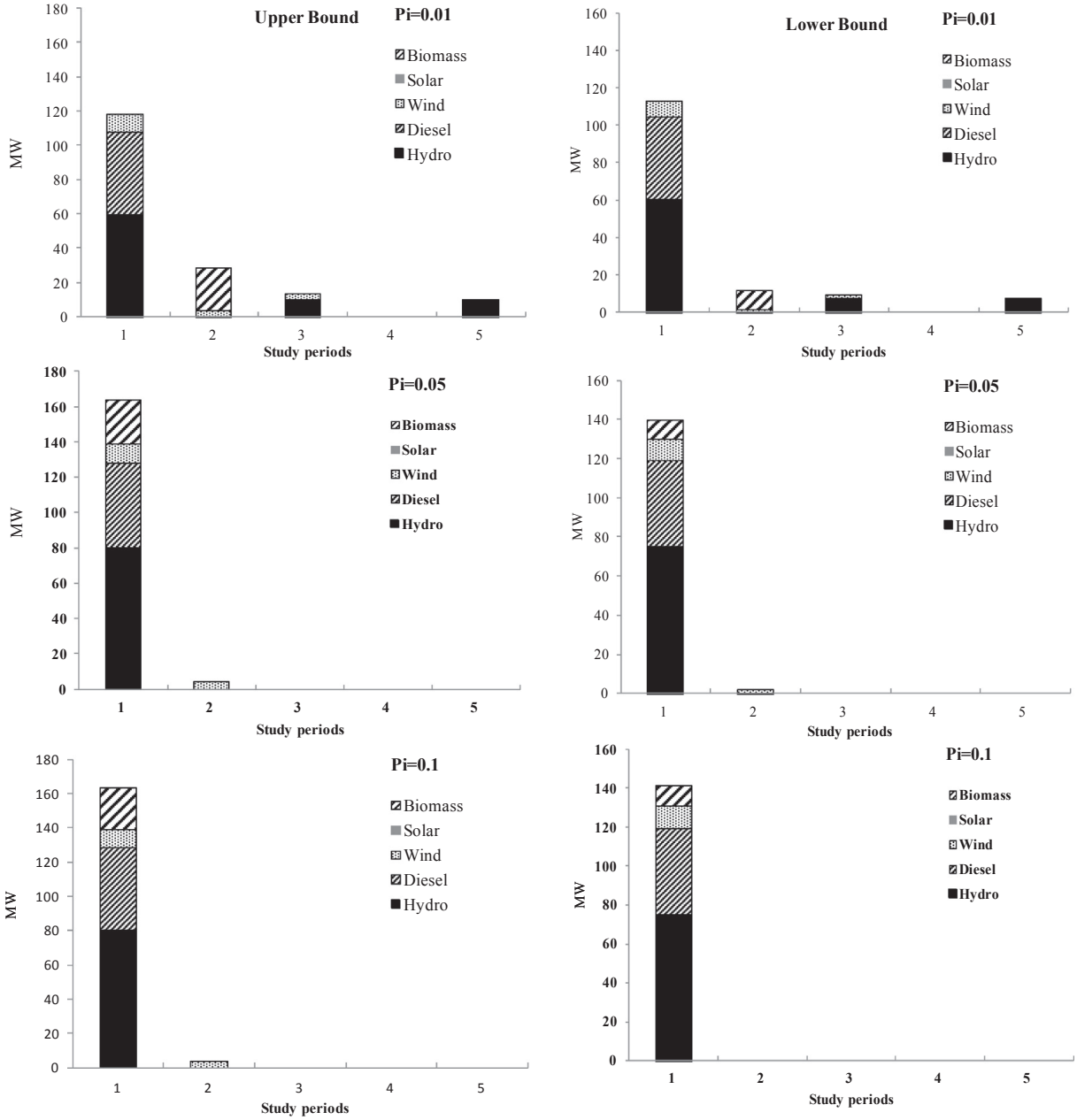

Fig. 6. Capacity expansion scheme under different P_i values of (a) upper bound and (b) lower bound.

both $P_i = 0.05$ and $P_i = 0.1$. This means that with a higher possibility of constraints violation under $P_i = 0.1$, the expansion will be executed even if the conditions for wind and solar are not satisfied. Fig. 6 also indicates that the expansion of wind and biomass power capacity will be similar to hydropower. The expansion activity in periods 2 and 3 will occur under a higher P_i value, which means a smaller possibility of being subject to electrical capacity constraints and, therefore, more system risks. Expansion of diesel plant capacity would not change, because the maximum capacity and electricity generated will not provide sufficient resources. Additionally, solar power's generating capacity will not be increased due to insufficient solar resources throughout the year in the Yukon. Therefore, it can be found that under a higher Pi lever, i.e. a higher chance of violating the capacity expansion constraints, the optimized results show an earlier timing for facility expansion. Policymakers can choose from different alternatives depending on their acceptance of system risk. If a conservative policy is required, then a higher Pi lever, i.e. lower system risky alternatives (with higher system costs) should be considered primarily. Otherwise, a higher risk (with lower system costs) will be accepted for a more progressive development.

5. Conclusion

In this study, an inexact chance-constrained mixed-integer model was developed for energy systems planning and GHG emissions mitigation management under uncertainties in the Yukon. Taking into consideration the policy interests in promoting the use of renewable energy and addressing climate change through a regional energy system, the detailed mathematical model describes the optimal energy system with supply schemes and restricted GHG emission outputs. In real-world case studies, uncertainties are complicated by various sources of imprecise information, including the energy market, demand projections, the characteristics of energy resources, and socio-economic conditions. To deal with these uncertainties, the model integrates

interval-parameter, chance-constrained, mixed-integer programming into the energy system framework. The proposed model employs mixed-integer linear programming to determine the optimal capacity expansion of generating facilities to meet the demand, interval linear programming to tackle the system uncertainties expressed as interval numbers, and chance-constrained programming under a series of P_i levels to evaluate the system reliability under different levels of available renewable energy. A lower P_i level represents higher satisfaction of system constraints and availability of energy resources. Thus, the generating facilities can be expanded to make more energy available. A higher P_i level represents higher violations of the system constraints and lower availability of energy resources in each study period. The interval solutions under different P_i levels (P_i = 0.01, 0.05, 0.1) can be obtained and used for decision alternatives.

The proposed model was implemented in the Yukon Territory to plan the optimal energy system. Three scenarios and one BAU case were provided based on local policies and regulations. Tradeoffs among system costs, GHG emissions control, and renewable energy utilization were analyzed. The results indicated that the developed models could support decision making in energy systems and environmental management in Yukon. The advantage of this model is its ability to reflect uncertainties expressed in multi-uncertainty and the dynamics of capacity expansion alternatives in the energy system planning process.

Acknowledgement

This research was supported by the National Key Research and Development Plan (2016YFC0502800, 2016YFA0601502), the Natural Sciences Foundation (51520105013, 51679087), the 111 Program (B14008) and the Natural Science and Engineering Research Council of Canada. The data used in this paper are available from the authors upon request. The authors would also like to express special thanks to the editor and the anonymous reviewers for their constructive comments and suggestions in improving the quality of this paper.

References

[1] Suganthi L, Samuel AA. Energy models for demand forecasting—A review. Renew Sustain Energy Rev 2012;16(2):1223–40.
[2] Assessment ACI. Impacts of a warming arctic-arctic climate impact assessment. Impacts of a warming arctic-arctic climate impact assessment, by arctic climate impact assessment, pp. 144. ISBN 0521617782. Cambridge, UK: Cambridge University Press, December 2004. p. 144.
[3] Hassol SJ. Impacts of a warming Arctic-Arctic climate impact assessment. Cambridge University Press; 2004.
[4] IPCC, Fifth assessment report (AR5). Cambridge: Cambridge University Press; 2014
[5] Dong C, Huang GH, Cai YP, Xu Y. An interval-parameter minimax regret programming approach for power management systems planning under uncertainty. Appl Energy 2011;88(8):2835–45.
[6] Nie S, Huang CZ, Huang GH, Li YP, Chen JP, Fan YR, et al. Planning renewable energy in electric power system for sustainable development under uncertainty–A case study of Beijing. Appl Energy 2016;162:772–86.
[7] Huang CZ, Nie S, Guo L, Fan YR. Inexact fuzzy stochastic chance constraint programming for emergency evacuation in Qinshan nuclear power plant under uncertainty. J Environ Inform (Int Soc Wnciron Inform Sci) 2017;30(1):63–78.
[8] Huang GH, Loucks DP. An inexact two-stage stochastic programming model for water resources management under uncertainty. Civil Eng Syst 2000;17(2):95–118.
[9] Li Z, Huang G, Cai Y, Li Y. Inexact optimization model for supporting waste-load allocation in the Xiangxi River basin of the Three Gorges reservoir region, China. J Comput Civil Eng 2014;29(6):04014093.
[10] Zhou Y, Huang G, Baetz BW. Multilevel factorial fractional programming for sustainable water resources management. J Water Resour Plann Manage 2016;142(12):04016063.
[11] Cheng G, Huang G, Dong C, Xu Y, Chen J, Chen X, et al. Distributed mixed-integer fuzzy hierarchical programming for municipal solid waste management. Part II: scheme analysis and mechanism revelation. Environ Sci Pollut Res 2017;24(9):8711–21.
[12] Chen B, Li P, Wu HJ, Husain T, Khan F. MCFP: A Monte Carlo simulation-based fuzzy programming approach for optimization under dual uncertainties of possibility and continuous probability. J Environ Informatics 2017;29(2):88–97.
[13] Li YP, Nie S, Huang CZ, McBean EA, Fan YR, Huang GH. An integrated risk analysis method for planning water resource systems to support sustainable development of an arid region. J Environ Informatics 2017;29(1):1–15.
[14] Li YP, Huang GH, Huang YF, Zhou HD. A multistage fuzzy-stochastic programming model for supporting sustainable water-resources allocation and management. Environ Modell Software 2009;24(7):786–97.
[15] Ren H, Zhou W, Nakagami KI, Gao W, Wu Q. Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects. Appl Energy 2010;87(12):3642–51.
[16] Li Z, Huang G, Zhang Y, Li Y. Inexact two-stage stochastic credibility constrained programming for water quality management. Resour Conserv Recycl 2013;73:122–32.
[17] Zhou Y, Huang G, Zhu H, Li Z, Chen J. A factorial dual-objective rural environmental management model. J Cleaner Prod 2016;124:204–16.
[18] Miara A, Macknick JE, Vörösmarty CJ, Tidwell VC, Newmark R, Fekete B. Climate and water resource change impacts and adaptation potential for US power supply. Nat Clim Change 2017;7(11):793.
[19] Smith BR. Modelling New Zealand's energy system. Eur J Oper Res 1980;4(3):173–84.
[20] Groscurth HM, Kümmel R, Van Gool W. Thermodynamic limits to energy optimization. Energy 1989;14(5):241–58.
[21] Tiris M, Atagunduz G, Dincer I. Energy, economy and environment modelling: Applications for Turkey. Energy 1994;19(9):1005–9.
[22] Lin QG, Huang GH, Bass B, Nie XH, Zhang XD, Qin XS. EMDSS: An optimization-based decision support system for energy systems management under changing climate conditions – An application to the Toronto-Niagara Region, Canada. Expert Syst Appl 2010;37(7):5040–51.
[23] Keirstead J, Jennings M, Sivakumar A. A review of urban energy system models: Approaches, challenges and opportunities. Renew Sustain Energy Rev 2012;16(6):3847–66.
[24] Wijayatunga PDC, Fernando WJLS, Shrestha RM. Greenhouse gas emission mitigation in the Sri Lanka power sector supply side and demand side options. Energy Convers Manage 2003;44(20):3247–65.
[25] Song H, Dotzauer E, Thorin E, Guziana B, Huopana T, Yan J. A dynamic model to optimize a regional energy system with waste and crops as energy resources for greenhouse gases mitigation. Energy 2012;46(1):522–32.
[26] Tong LI, Saminathan R, Chang CW. Uncertainty assessment of non-normal emission estimates using non-parametric bootstrap confidence intervals. J Environ Inf 2016;28(1):61–70.
[27] El-Fadel M, Chedid R, Zeinati M, Hmaidan W. Mitigating energy-related GHG emissions through renewable energy. Renew Energy 2003;28(8):1257–76.
[28] Blackhurst MF. Achieving realistic energy and greenhouse gas emission reductions in US cities (Doctoral dissertation, Carnegie Mellon University); 2011
[29] Yu L, Li YP, Huang GH, Fan YR, Yin S. Planning regional-scale electric power systems under uncertainty: A case study of Jing-Jin-Ji region, China. Appl Energy 2018;212:834–49.
[30] Galán-Martín A, Pozo C, Azapagic A, Grossmann IE, Mac Dowell N, Guillén-Gosálbez G. Time for global action: an optimised cooperative approach towards effective climate change mitigation. Energy Environ Sci 2018.
[31] Zhou X, Huang G, Zhu H, Chen J, Xu J. Chance-constrained two-stage fractional optimization for planning regional energy systems in British Columbia, Canada. Appl Energy 2015;154:663–77.
[32] Mazur V. Fuzzy thermoeconomic optimization of energy-transforming systems. Appl Energy 2007;84(7–8):749–62.
[33] Marano V, Rizzo G, Tiano FA. Application of dynamic programming to the optimal management of a hybrid power plant with wind turbines, photovoltaic panels and compressed air energy storage. Appl Energy 2012;97:849–59.
[34] Anasis JG, Khalil MAK, Butenhoff C, Bluffstone R, Lendaris GG. A combined energy and geoengineering optimization model (CEAGOM) for climate and energy policy analysis. Appl Energy 2018;218:246–55.
[35] Government of Yukon, Yukon Bureau of Statistics, Yukon Energy Facts, 2013. http://www.eco.gov.yk.ca/pdf/energy_2013.pdf [accessed 20.06.2017].
[36] Government of Yukon, Yukon Bureau of Statistics. http://www.eco.gov.yk.ca/stats/1467.html [accessed 20.06.2017].
[37] Willis BL. The environmental effects of the Yukon Gold Rush 1896-1906: Alterations to Land, Destruction of Wildlwec, and Disease (Doctoral dissertation, The University of Western Ontario London); 1997.
[38] Statistic Canada, annual demographic statistics. CANSIM (2017). http://www5.statcan.gc.ca/cansim/a26?lang=eng&retrLang=eng&id=0510001&&pattern=&stByVal=1&p1=1&p2=37&tabMode=dataTable&csid=.
[39] Statistics Canada. Energy statistics handbook. Catalogue no. 57-601-X. January 2009.
[40] National energy board, energy use in Canada's North: an overview of Yukon, Northwest Territories, and Nunavut; 2011. https://www.neb-one.gc.ca/nrg/ntgrtd/mrkt/archive/2011nrgsncndnrthfct/nrgsncndnrthfct-eng.pdf.
[41] Scudder GGE. Environment of the Yukon. Insects of the Yukon. Biological survey of Canada (terrestrial arthropods), Ottawa; 1997. p. 13–57.
[42] Wahl HE. Climate of Yukon (No. 40). Canadian Government Publ. Centre]; 1987.
[43] Karanasios K, Parker P. Recent developments in renewable energy in remote aboriginal communities, Yukon, Canada. Pap Can Econ Dev 2016;16:29–40.
[44] Yukon energy 20–year resource plan: 2011-2030 (2011). Yukon Energy Corporation. http://www.yukonenergy.ca/downloads/db/1184_2012%20Resource

%20Plan%20Overview.pdf.
[45] Cai YP, Huang GH, Yang ZF, Tan Q. Identification of optimal strategies for energy management systems planning under multiple uncertainties. Appl Energy 2009;86(4):480–95.
[46] Lin QG, Huang GH. Planning of energy system management and GHG-emission control in the Municipality of Beijing—An inexact-dynamic stochastic programming model. Energy Policy 2009;37(11):4463–73.
[47] Huang GH, Baetz BW, Patry GG. Grey integer programming: an application to waste management planning under uncertainty. Eur J Oper Res 1995;83(3):594–620.
[48] Cheng GH, Huang GH, Dong C. Interval recourse linear programming for resources and environmental systems management under uncertainty. J Environ Inform (Int Soc Environ Inform Sci) 2015.